I specialize in microeconomic theory and behavioral economics. I have recently studied the implications of multi-agent learning in settings with populations of rational or behavioral learners. My investigation of behavioral learning focuses on the interaction between behavioral biases and features of the learning environments, while my research on rational learning centers around the implications of non-equilibrium learning for equilibrium refinements. An emphasis on the dynamics of learning unifies both areas of my work.

My job-market paper [1] studies the endogenous learning dynamics of people who expect systematic reversals from sequential random events, a bias known as the “gambler’s fallacy.” Biased agents act one at a time, facing the same optimal-stopping problem in turn. For concreteness, think of HR managers conducting sequential interviews before hiring a candidate. Agents are uncertain about the problem’s draw-generating distribution (e.g. the distribution of talent in the labor pool) and must use their predecessors’ histories (e.g. senior managers’ recruiting experience) to learn parameters of this distribution. Agents rationally stop when early draws are deemed “good enough” (e.g. when early candidates are strong). This directional censoring effect implies that predecessors’ histories contain negative streaks but not positive streaks. In accordance with the gambler’s fallacy, biased learners understate the likelihood of consecutive below-average draws. Asymmetrically censored data therefore cause over-pessimistic inference about the distribution’s mean and lead to stopping too early. The interaction between the statistical bias and data censoring is essential for mislearning — agents would learn correctly if either obstacle was removed. The severity of data censoring is also endogenous, as it depends on the predecessors’ stopping strategies (i.e. thresholds for “good enough”). When agents act in large generations, a positive-feedback loop between distorted beliefs and distorted stopping strategies drives deterministic generational learning dynamics. If the present generation lowers its acceptance thresholds, future learners will become more surprised by the lack of positive reversals in the present generation’s histories, leading to more pessimistic inferences and even lower future acceptance thresholds.

My joint work with Krishna Dasaratha [2] considers a different behavioral bias in the context of sequential social learning. Agents live in a social network and act one at a time, making guesses about a state of the world based on: (i) the guesses of network neighbors who acted before, and (ii) their own private signals. Agents exhibit inferential naiveté, wrongly believing that their neighbors acted solely on private information. We show that almost all networks lead to imperfect learning for naive agents, then examine how different network structures lead to differentially inefficient outcomes through their interactions with the bias. To do this, we go beyond existing results and compute the exact probability of correct learning on a given network. The probability of correct learning is lower on denser networks. We confirm this prediction using an experiment, finding that people’s accuracy gain from learning is twice as large on sparser networks. In partially segregated networks, divergent early signals can lead to persistent disagreement between groups — a common empirical phenomenon that is difficult to reconcile with rational models of social learning.

In the area of rational multi-agent learning, I have completed a cluster of interrelated projects on the refinement implications of learning-in-games, coauthored with Drew Fudenberg. Based on the idea
that equilibrium originates from learning, these projects refine equilibrium prediction sets by eliminating equilibria to which learning cannot converge. Suppose large populations of patient, long-lived senders and receivers are randomly matched to play a signaling game each period. Young senders are uncertain about how receivers react to different signals, generating experimentation incentives. In [3], we compare the relative frequencies with which different sender types rationally experiment with a given (possibly off-path) signal during the learning process. This comparison leads to a compatibility-criterion restriction on the receivers’ off-path beliefs. In particular, every learning outcome satisfies the Intuitive Criterion. In [4], we obtain further refinements by assuming that agents know others’ rationality and utility functions. (These projects apply our statistical results on Bayesian inference after rare events [5], in collaboration with Lorens Imhof. The “rare events” in question correspond to the uncommon but positive-probability events of receivers observing “off-path” signals during the learning process.) In [6], we consider general games and propose a tremble-based solution concept with cross-player restrictions on the relative magnitudes of trembles. Our solution concept selects intuitive equilibria in games where other tremble-based concepts have no bite. We show that rational learning and some near-optimal heuristics imply our tremble restrictions.

Much of my work has revolved around analyzing learning dynamics, both as tools for studying the limit properties of learning and as objects of interest in their own right. For instance, [3] derives and compares the optimal experimentation dynamics of different types of senders in learning to play a signaling game. This comparison proves crucial in deducing which beliefs and equilibria can arise in the long-run limit of learning. As another example, the large-generations environment in [1] allows me to trace out the exact evolution of beliefs and behavior in each generation. Such medium-run dynamics paint a richer picture of how welfare evolves over time for biased learners and clarify how endogenous censoring amplifies the misinferences of early agents. I plan to continue exploring this theme in future work.

References


